DEEP LEARNING BASED DRAGON FRUIT CLASSIFICATION

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering.

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APPROVAL

This Project titled "Deep Learning Based Dragon Fruit Classification", was submitted by Md. Sazzat Hossen, Md. Ashraful Momenin & Israt Islam to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 05 Wednesday, January 2022.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Abbas Ali Khan, Sr. Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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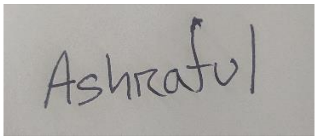

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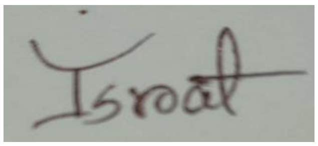

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ABSTRACT

The dragon fruit is now widely grown all over the world. Its popularity is growing as a result of its nutritious benefits. The predominant colors are red and white. However, because it appears to be the same from the outside, it cannot be identified. The CNN approach is used to detect dragon fruit in this research. For this type of dragon fruit, a detection approach based on shape features is proposed. Xceptional Model used for fruit shape features, which is utilized to detect fruits in potential locations and further locate fruit positions. Images captured under various illuminations were used to test the suggested strategy. The ability to detect fruits covered at various levels is also evaluated. The accuracy values are all greater than 94.89% percent, indicating that the suggested approach can detect a large percentage of covered fruits.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Dragon Fruit is one of the world's most delicious fruits. It was created in the United States and Africa at first, but it is currently produced commercially all over the world. Pitaya, also known as the strawberry pear or dragon fruit, is a sweet and crisp tropical fruit. The fruit derives from a Hylocereus cactus, which has about 20 different species. The fruit is available in four varieties: three with pink skin, one with white flesh, one with red flesh, and one with purple flesh. However, the predominant colors are red and white. Dragon fruit is a low-calorie, high-fibre fruit that also has a good number of vitamins and minerals. Dragon fruit contains 38.9mg per 100g of pulp Magnesium, a natural tranquillizer that can generally provide a good night sleep. Fruits have high fibre content, as well as vitamins, minerals, and antioxidants. Dragon fruit pulp contains some of the most powerful antioxidants, which help to protect our cells from harm. Dragon fruit is one of the few fresh fruits that contain iron. The fruit's peel is used as a thickening and culinary coloring. This fruit looks the same from the top but it has white and red color inside. We will discuss how to identify the color inside by looking at its color and size from our research.

1.2 Two Common Types of Dragon Fruit

- Red-Skinned Fruit With Red Flesh
- Red-Skinned Fruit With White Flesh

1.2.1 Red-Skinned Fruit With Red Flesh

Hylocereus costaricensis is the scientific name for a red-skinned dragon fruit with crimson meat. Red Dragon fruits are produced by long, thin, vining cactuses that grow up trees, fences, and buildings. On the outside, red Dragon fruits resemble their white-fleshed counterparts. It can reach a length of up to 10cm. The vivid magenta flesh of the Red Dragon fruit is due to a substance called betacyanin. The pulp has a kiwi-like texture and is studded with little black edible seeds. The first categorization relates to Costa Rica, the company's native nation. The red dragon fruit is juicier and sweeter. The red dragon fruit is typically spherical, with thick green scales. For millennia, the indigenous peoples of

Costa Rica and the surrounding territories have used red dragon fruit. Red dragon fruit flowers are brighter in color than white dragon fruit flowers, and they have more thrones on their branches. Red dragon fruit has a higher antioxidant content than other fruits.

Figure 1: Red-skinned fruit with red flesh

1.2.2 Red-Skinned Fruit With White Flesh

Hylocereus undatus is the scientific name for a red-skinned dragon fruit with white meat. It's the most common dragon fruit. The white-skinned dragon fruit has fewer ears that are spaced further apart. The shape of the white dragon fruit is generally oblong. The flavor of whitish dragon fruit is usually modest. The flowers of the white-skinned dragon fruit are a lighter red color, but they can also be green or yellow. Fruit with white flesh has fewer branches than those with red flesh. Diabetic individuals will benefit from white dragon fruit.

Figure 2: Red-skinned fruit with white flesh

1.3 Machine Learning

Machine learning is a subfield of artificial intelligence. Artificial Intelligence (AI) is a type of artificial intelligence that allows frameworks to take in and improve information without being explicitly changed. It's a study topic that allows computers to learn without being explicitly programmed. Machine learning allows a user to send a large amount of data to a computer program, which analyzes it and generates data-driven recommendations and judgments based only on the data provided. The field of artificial intelligence (AI) is concerned with the creation of computer programs that can obtain information and use it to solve problems on their own. The process of AI prediction developing a model based on example data in order to colonize prospects or choices without being clearly designed to do so is known as "preparing information." Machine learning centered on the creation of computer programs that could access data and learn for themselves. When doing traditional calculations is difficult or impossible, machine learning calculations are employed in a number of applications, such as email screening and PC vision.

1.4 Machine Learning Methods

In general, there are two types of machine learning methods. Machine learning is an AI approach that teaches a machine to think like a human. Unsupervised learning, on the other hand, does not seek to produce output in response to a specific input; rather, it seeks to uncover patterns in data. We need to look into these methods more.

1.4.1 Supervised Learning

Supervised machine learning is a subcategory of machine learning and artificial intelligence. In a supervised learning model, the algorithm learns on a labelled dataset, which gives an answer key that the system may use to evaluate its correctness on training data. The supervised learning process is simpler, and the results are more accurate and consistent. It gets its responsiveness from a set of preparing models' marked preparing intelligence component. In supervised learning, a training set is used to teach models to produce the desired output. The model can improve over time because this training dataset contains both accurate and wrong outputs. Image and object identification, predictive analytics, customer sentiment analysis, and spam detection are just a few of the commercial applications that may be constructed and upgraded utilizing supervised learning models.

1.4.2 Unsupervised Learning

Unsupervised learning gives the algorithm unlabeled input to sort through by extracting features and patterns on its own. It looks for patterns that can help solve clustering and association difficulties. Unsupervised learning tries to find the underlying structure of a dataset, categorize data based on similarities, and present the dataset in a compact manner. The model does not require any human supervision. It necessitated a vast amount of information. Because the algorithm is never trained on the given dataset, it has no idea what its characteristics are. The purpose of the unsupervised learning algorithm is to recognize visual elements independently. This job will be done by clustering the image collection into groups based on visual similarities using an unsupervised learning method. Because there is no labelled input data in unsupervised learning, it is used for more complicated problems than supervised learning.

1.5 CNN

An artificial neural network that uses convolutional neural networks is a type of artificial neural network. The convent is another name for CNN. It is used to evaluate visual images using a grid to process data. Convolutional neural organization (CNN) is a well-known deep learning technique that teaches a model how to perform classification tasks from photos, video, text, or audio. Each layer of a convolutional neural network defines how to distinguish various highlights in a picture, and each layer can have tens or hundreds of them. Channels are applied to each preparation picture at different targets, and the yield of each convolved picture is used as the contribution to the next layer. CNN’s are very useful for detecting patterns in images so that articles, faces, and scenes may be recognized. It's very useful for seeing patterns in photos, as well as capturing articles, faces, and scenes. They work directly from image data, adorning images with examples and removing the need for human element removal. CNN’s operate by dividing down an image into smaller groupings of pixels known as filters. Each filter is a matrix of pixels, and the network performs a series of calculations on these pixels before comparing them to pixels in a certain pattern. The channels might start with very basic highlights like brilliance and edges and work their way up to highlights that clearly define the item.

1.6 Deep Learning

Deep learning is a subset of machine learning, which can be thought of as a subset of machine learning. It is a field concerned with computer algorithms that learn and evolve on their own. Machine learning utilizes simpler principles, but deep learning uses artificial neural networks, which are designed to replicate how people think and learn. The complexity of neural networks was previously limited by processing capacity. Thanks to improvements in Big Data analytics, larger, more powerful neural networks are now conceivable, allowing computers to watch, learn, and react to complex events faster than humans. Deep learning has aided image categorization, language translation, and speech recognition. It can solve any pattern recognition challenge without the assistance of a human.

1.7 Computer Vision

Computer vision is an artificial intelligence field that allows computers to learn to explain and comprehend the visual world. Technically, machines use sophisticated software algorithms to recover visual information, handle it, and illustrate outputs. It is particularly useful for an item classification, identification, and tracking. Object classification is a technique for parsing visual content and assigning a category to an object in a photograph or video. Object recognition is a technique for analyzing visual content and identifying any object in a photograph or video. It analyses videos to locate items that satisfy the search parameters and track their movement in object tracking.

1.8 Objectives

Our major goal in this project is to create a model that can recognize Dragon species; presently, machine learning is a common technique for image recognition. In this study, we combined the Color and Shape Features model with certain algorithms, and we used the dataset to train our model for accurately recognizing Dragon species.

1.9 Motivation

Bring about a revolution in the world of agriculture. It was less likely to be incorrect, and it decreased human error. It will be very beneficial to diabetic individuals. To make a more informed decision.

1.10 Expected Outcome

The Dragon's Fruit Mainly There are two species on the globe. It is absolutely unknown to the general public. In this document, we want to enlighten others about this. Everyone will be aware of two dragon species as a result of this research. It is simple to detect without the use of human touch.

CHAPTER 2
BACKGROUND

2.1 Related Work

Despite the fact that dragon characterization is a fascinating and promising work with numerous applications however shockingly there has not been any work detailing the characterization of dragon organic products. Despite the fact that there were not many works detailing dragon recognition for different applications. We quickly present them as follows.

- Most mature apple fruits have green and pale yellow skins, making machine vision fruit detection more difficult. For this type of apple fruit, a detection approach based on color and form features has been presented. Clustering in a linear iterative fashion is simple and straightforward (SLIC) is designed to split orchard pictures into super-pixel blocks. The color characteristic taken from candidate regions is determined using blocks, which can filter out a high percentage of non-fruit blocks and enhance the accuracy of detection. The next step is to use the histogram of oriented gradient (HOG) to describe the shape of fruits, which is then used to discover fruits in potential regions and further determine their position. Images captured under various illuminations were used to test the suggested strategy. Recall, precision, and F1 have average values of 89.80 percent, 95.12 percent, and 92.38 per cent, respectively. The ability to detect fruits covered at various levels is also evaluated. The recall values are all greater than 85%, indicating that the suggested approach can detect a large percentage of covered fruits. In comparison to the pedestrian identification approach and the quicker region-based convolutional neural network (RCNN), the suggested method has the best performance and marginally outperforms the faster RCNN. However, the proposed method is not noise-resistant, and one image takes 1.94 seconds, which is slower than the quicker RCNN [1].

- Tomato (Solanum Lycopersicon) is the scientific name for the plant Solanum Lycopersicon. There are many tomato varieties, many of which are half breeds, but they may all be divided into seven types. Despite the fact that tomatoes are commonly referred to and used as vegetables in cooking, they are all products of the plant Solanum Lycopersicon. Tomatoes are a common vegetable in our country. Which has been linked to a variety of health outcomes, including a lower risk of coronary artery disease and threatening development. They also contain high levels of vitamin C, potassium, folate, and vitamin K. In this paper, we propose a convolutional neural network (CNN)-based technique for recognizing two tomato species from 4000 distinct images: Bradly and WA Cherry. We used a CNN model and used models to break down the acknowledgement rates for better experimentation. For this project, Convolutional Neural Network (CNN) calculations were used, which is a machine learning method widely used in image recognition. When CNN-driven tomato order apps are used in characterization mechanization, the results show that people can correctly identify the type of tomato. Here, a fuzzy filter was applied to remove image noise. On the test set, the constructed model achieved a precision of 98.44 per cent, demonstrating the methodology's viability [2].

- In the agriculture area, image processing technology is widely used. The majority of it was applied to a robot that might be used to pick fruit and examine vehicles. To attain near-human levels of recognition, computer vision faces significant challenges in the areas of identification and categorization. The classification of fruits and vegetables is useful in supermarkets and can be used in computer vision for the automatic sorting of fruits from a set of various types of fruits. The goal of this project is to create an automated tool that can detect and classify mango fruits using digital image analysis based on shape, size, and color features. To begin, pre-processing techniques will be used to create a binary picture from digital photographs of several mango fruits utilizing texture analysis and morphological procedures. The processed photos will then be further categorized using an appropriate classification approach. The Image Processing Toolbox was used to identify and classify fruits using MATLAB as the programming tool. The proposed method can be utilized to detect obvious faults, stems, size, and form of mangos, as well as classify them quickly and accurately [3].

- Color is one of the criteria used to determine the level of ripeness because each level of fruit development has a different color level. At the moment, the dragon fruit is solely classed based on a visual examination of the human eye's skin color. The goal of this research is to categorize dragon fruit using image processing and the naive Bayes method in the HSV color space. The RGB color feature was employed in this study, and it was transformed to an HSV value, which was subsequently classified using the empirical Bayes technique. There were 120 training photos and 30 test images used in this study. The accuracy percentage of the dragon fruit categorization utilizing the naive Bayes approach based on the HSV color space is 86.6 percent [4].

- Agriculture is a major source of revenue in many developing countries, including India, Indonesia, and others. The GDP (Gross Domestic Product) rate of agricultural products determines the economic development of these countries. However, food waste occurs as a result of miscalculations in the ripeness of fruits and vegetables. Many steps were taken in general to prevent food spoilage by meticulously tracking each stage of the vegetables and fruits, but this required a lot of human labour. And exhaustion non-climacteric fruits, such as the dragon fruit, require special attention because they must be harvested. After it has ripened and cannot be ripened after harvesting using ethylene, carbide, and other hastening ripening agents CO2 and other gases. So the paper uses the RESNET 152, a deep learning convolution neural network, to recognize the mellowness in the dragon fruit and when it's appropriate to harvest. Python and tensor flow were used to train the model. The developed structure was trained using images of the dragon fruit at various phases of mellowness and then tested with 100 new data using the region of convergence and the confusion matrix. The testing was done with a variety of epoch numbers ranging from 10 to 500. In terms of accuracy and loss in training and testing, the findings obtained were more accurate than the VGG16/19 [5].

- Mangifera Indica, sometimes known as mango, is a drupe with over 500 kinds found all over the world. In 2017, India produced 19.5 million metric tons of mango. Mango has been designated as Bangladesh's national tree, and the government has placed endemic mango species in the country's geographical index (GI). Computer vision has become a crucial role in recognizing distinct breeds. In this paper, we propose a convolutional neural network (CNN)-based approach for recognizing five mango species from 15000 distinct images: Choshu, Fazli, Hari The majority of agricultural products produced in developing countries are currently exported to a variety of countries throughout the world. As a result, these products must be classified according to distinct standards. Dragon fruit is regarded as the fruit with the greatest export rate in Vietnam. Currently, dragon fruit classification is done by hand, which results in low-quality classification and expensive labour expenses. As a result, based on a convolutional neural network, this paper offers an autonomous dragon fruit classification system that uses non-destructive measurements (CNN). This classification method identifies the external aspects of dragon fruits using a combination of a machine learning model and image processing using a convolutional neural network; the fruits are then classed and assessed by groups. The system recognizes the dragon fruit by extracting the objects and using the signal from the loadcell to calculate and identify the number of dragon fruit in each group. To train the model, the training data is acquired from the dragon fruit processing system, which has a dataset of photos obtained from over 1287 dragon fruits. The classification of processing speed and accuracy are the two most essential factors in this system. The findings suggest that the classification system is very effective. With existing dragon fruit varieties, the method works well. The system's processing speed boosts the sorting capacity of export packing facilities in Vietnamese manufacturers to six times that of the manual approach, with an accuracy of more than 96 per cent. vanga, Lengua, and Rupali. We used three distinct CNN models and examined the recognition rates using various criteria for better experimentation. We used traditional performance measurements including precision, recall, F1-score, ROC, and accuracy to assess performance. The third model, with a score of 92.80%, outperformed the other two models in terms of accuracy [6].

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CHAPTER 3
METHODOLOGY

3.1 Methodology

We've focused on the model we've offered for ordering numerous natural items, their variations, and the nature of organic products in this part. In a visual format, Figure.3 displays the complete cycle of detecting organic things using CNN (Xceptional). The basic techniques indicated in the subsection below were used to compile the examination work.

3.2 Proposed Methodology

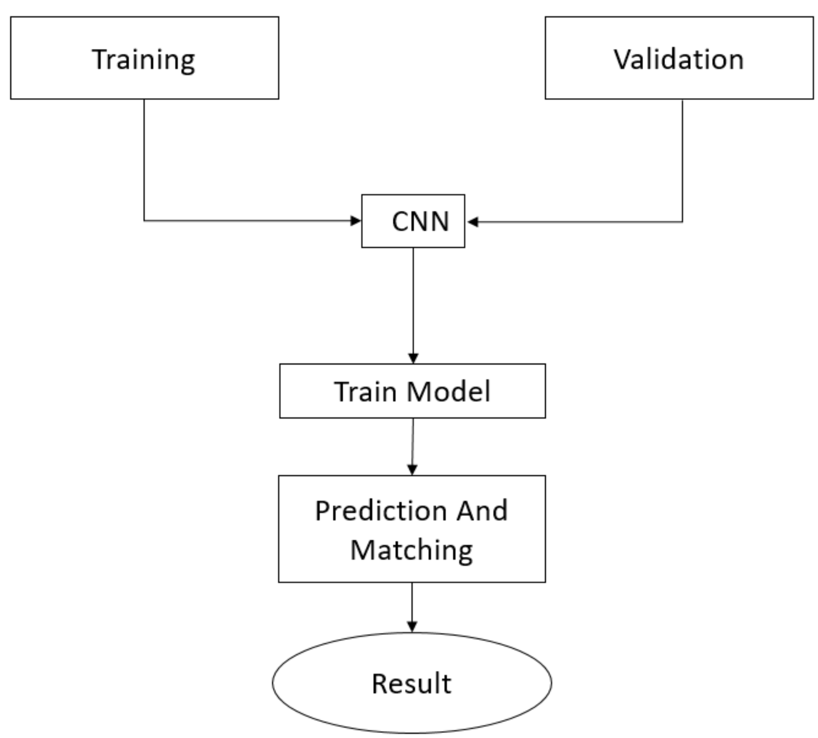

Figure 3: The proposed methodology

3.2.1 Capturing Images

Here all of the images are genuine. Which are picked by us. Images are picked in different places and situations from the market within a few days. Using our mobile phone. The size of the images is around 218, 771 bytes. In our research, we have captured images of 2 breeds of dragons shown in Figure 4.

Figure 4: Dragon Fruit

3.2.2 Dataset

To yield the most ideal execution from our CNN model we have gathered a huge dataset having 1000 pictures around 500 pictures for each example class. The pictures are isolated into preparing and approval set utilizing the traditional holdout strategy. There are many types of dragons, but the data set provided only two types of dragons, as it contains 400 training images and 50 images for testing. We divided the data into training (85%), validation (15%).

3.2.3 Xception Model

Francois Cholet proposes the exception Model. The xception is an expansion of the Inception Architecture that uses depth-wise Separable Convolutions to replace the regular Inception modules. The exception model is a 71 layer deep CNN. Consider a convolution layer with ten 5x5 filters acting on a tensor of size (1x10x10x100). Each of the ten filters has the shape (5x5x100) and produces the output by sliding over the input tensor. As it moves over the input, each of the 5x5 filters covers the entire channel dimension (the complete 100). As a result, a typical convolution operation takes into account both the spatial (height and breadth) and channel dimensions.

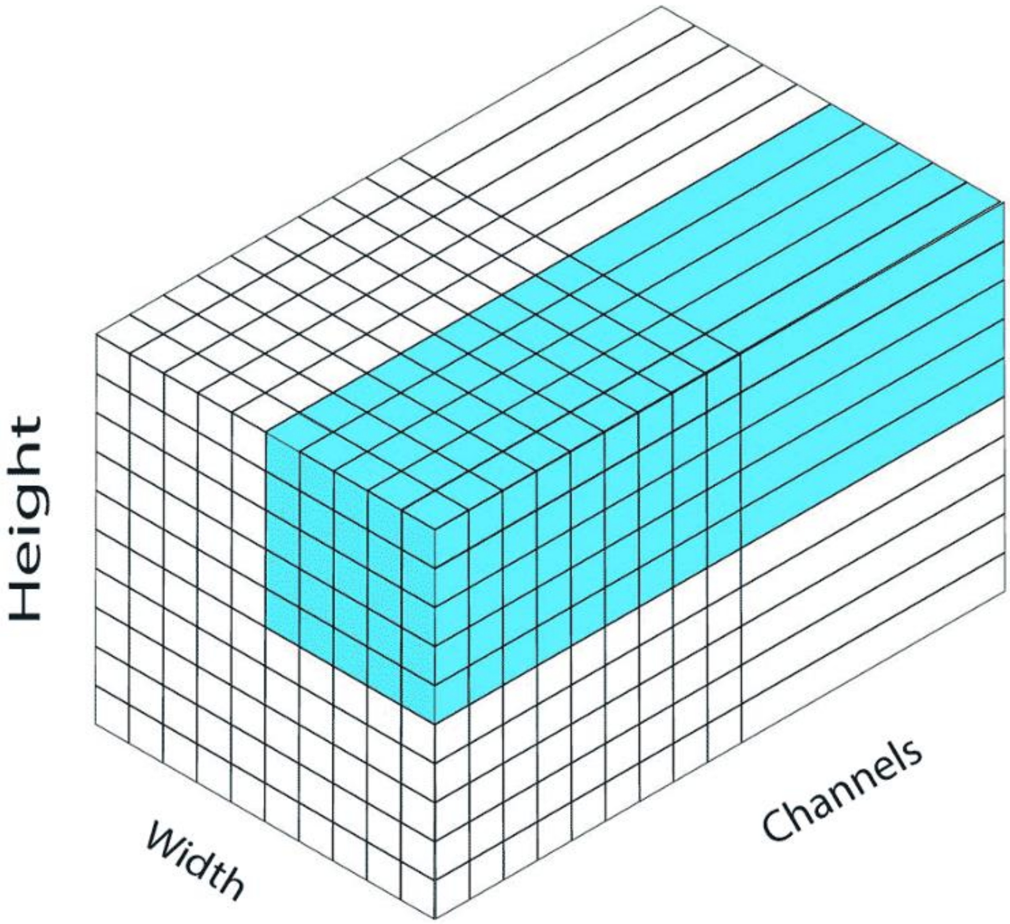

Figure 5: A 5x5 convolution filter sliding over a (10x10x100) tensor

A depth wise separable layer is made up of two functional pieces that divide the work of a traditional convolution layer. Depthwise convolution and pointwise convolution are the two sections. We'll go over each one individually.

3.2.3.1 Depthwise Convolution

Consider a depthwise convolution layer with 3x3 filters operating on a form tensor as an example (1x5x5x5). For the sake of simplicity, we'll remove the batch dimension because it makes no difference and treats it as a (5x5x5) tensor. Five 3x3 filters will be used in our depthwise convolution, one for each channel of the input tensor. And each filter will slide spatially through a single channel, generating the channel's output feature map. The output tensor will have the same number of channels as the input tensor because the number of filters is equal to the number of input channels. Let's keep the stride at 1 and avoid any zero paddings in the convolution procedure.

$$H = \frac{(\text{Height} - \text{FilterSize} + 2^*\text{Padding})}{\text{Stride}} + 1$$

$$W = \frac{(\text{Width} - \text{FilterSize} + 2^*\text{Padding})}{\text{Stride}} + 1$$

Figure 6: Output Height and Width calculation after applying a convolution

According to the output size formula after convolution, our (5x5x5) tensor will become a (3x3x5) tensor. The graphic below will help you understand the concept!

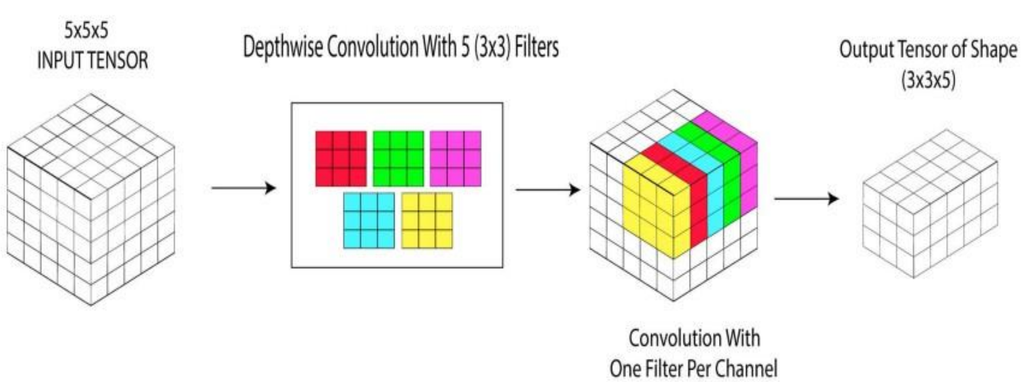

Figure 7: Illustration of Depthwise Convolution Operation

That's what Depthwise Convolution is all about. It's almost identical to how we accomplished the Xtreme convolution in the Inception, as you can see. The resultant tensor must then be fed into a pointwise convolution that performs cross-channel correlation. It simply means that it works over all of the tensor's channels.

3.2.3.2 Pointwise Convolution

A 1x1 convolution is also known as a pointwise convolution. A pointwise convolution can be used to enhance or reduce the depth (channel dimension) of a tensor. That's why it was utilized to minimize the depth before the 3x3 or 5x5 layers in the Inception block. We're going to use it to add depth here. But how do you do it? A normal convolution layer with a filter size of one is used for pointwise convolution (1x1 filters). As a result, after convolution, the spatial output size remains unchanged. The output tensor of the depthwise convolution has a dimension of in our example (8x8x5). If we apply 50 1x1 filters, we obtain the following result: (8x8x50). In the pointwise convolution, RELU activation is used. The Depthwise Separable Convolution is created by combining depthwise and pointwise convolutions. From here on out, we'll refer to it as DSC.

3.2.3.3 Xception Architecture

The author has divided the Xception Architecture into 14 modules, each of which consists of a collection of DSC and pooling layers. The entering flow, the middle flow, and the exit flow are the three groups of 14 modules. And there are four, eight, and two modules in each of the three groupings, correspondingly. At the end of the last group, i.e. the exit flow, completely connected layers can be added.

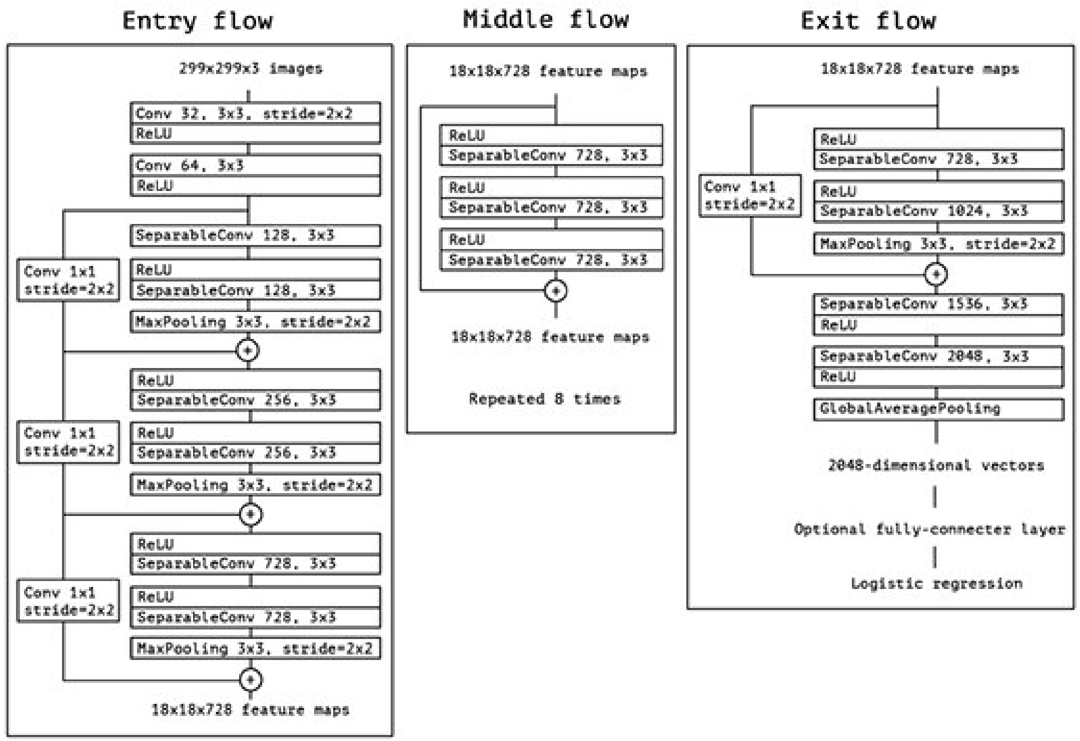

Figure 8. Xception architecture

CHAPTER 4

RESULT AND DISCUSSION

4.1 Pooling

When the included top is False, this is an optional pooling mode for feature extraction. None implies that the model's output will be the last convolutional block's 4D tensor output. Average indicates that global average pooling will be applied to the output of the last convolutional block, resulting in a 2D tensor as the model's output. The word max denotes that global maximum pooling will be used.

TABLE 1: MODEL SUMMARY

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 640, 640, 3)]	0	[]
block1_conv1 (Conv2D)	(None, 319, 319, 32)	864	['input_1[0][0]']
block1_conv1_bn (BatchNormalization)	(None, 319, 319, 32)	128	['block1_conv1[0][0]']
block1_conv1_act (Activation)	(None, 319, 319, 32)	0	['block1_conv1_bn[0][0]']
block1_conv2 (Conv2D)	(None, 317, 317, 64)	18432	['block1_conv1_act[0][0]']
block1_conv2_bn (BatchNormalization)	(None, 317, 317, 64)	256	['block1_conv2[0][0]']
block1_conv2_act (Activation)	(None, 317, 317, 64)	0	['block1_conv2_bn[0][0]']
block2_sepconv1 (SeparableConv2D)	(None, 317, 317, 128)	8768	['block1_conv2_act[0][0]']
block2_sepconv1_bn (BatchNormalization)	(None, 317, 317, 128)	512	['block2_sepconv1[0][0]']
block2_sepconv2_act (Activation)	(None, 317, 317, 128)	0	['block2_sepconv1_bn[0][0]']

```
block14_sepconv1_bn (BatchNorm  (None, 20, 20, 1536  6144      ['block14_sepconv1[0][0]']
alization)                      )

block14_sepconv1_act (Activati  (None, 20, 20, 1536  0         ['block14_sepconv1_bn[0][0]']
on)                             )

block14_sepconv2 (SeparableCon  (None, 20, 20, 2048  3159552   ['block14_sepconv1_act[0][0]']
v2D)                            )

block14_sepconv2_bn (BatchNorm  (None, 20, 20, 2048  8192      ['block14_sepconv2[0][0]']
alization)                      )

block14_sepconv2_act (Activati  (None, 20, 20, 2048  0         ['block14_sepconv2_bn[0][0]']
on)                             )

global_average_pooling2d (Glob  (None, 2048)        0          ['block14_sepconv2_act[0][0]']
alAveragePooling2D)

dense (Dense)                  (None, 1024)         2098176    ['global_average_pooling2d[0][0]'
                                                                ]

dense_1 (Dense)                (None, 1024)         1049600    ['dense[0][0]']

dense_2 (Dense)                (None, 512)          524800     ['dense_1[0][0]']

dense_3 (Dense)                (None, 1)            513        ['dense_2[0][0]']

==================================================================================================
Total params: 24,534,569
Trainable params: 3,673,089
Non-trainable params: 20,861,480
__________________________________________________________________________________________________
```

Figure 9: Model Summary

4.2 Epoch

```
Epoch 1/30
16/16 [==============================] - 4614s 305s/step - loss: 2.6379 - categorical_accuracy: 0.1251 - val_loss: 2.5529 - val_categorical_accuracy: 0.1455
Epoch 2/30
16/16 [==============================] - 663s 43s/step - loss: 2.3861 - categorical_accuracy: 0.2129 - val_loss: 2.2156 - val_categorical_accuracy: 0.2738
Epoch 3/30
16/16 [==============================] - 660s 42s/step - loss: 2.0245 - categorical_accuracy: 0.3297 - val_loss: 1.6898 - val_categorical_accuracy: 0.4455
Epoch 4/30
16/16 [==============================] - 657s 41s/step - loss: 1.5450 - categorical_accuracy: 0.4923 - val_loss: 1.2144 - val_categorical_accuracy: 0.6037
Epoch 5/30
16/16 [==============================] - 668s 42s/step - loss: 1.1752 - categorical_accuracy: 0.6079 - val_loss: 1.0262 - val_categorical_accuracy: 0.6520
Epoch 6/30
16/16 [==============================] - 646s 40s/step - loss: 0.9624 - categorical_accuracy: 0.6768 - val_loss: 0.7945 - val_categorical_accuracy: 0.7272
Epoch 7/30
16/16 [==============================] - 666s 42s/step - loss: 0.8467 - categorical_accuracy: 0.7136 - val_loss: 0.7543 - val_categorical_accuracy: 0.7333
Epoch 8/30
16/16 [==============================] - 663s 42s/step - loss: 0.7215 - categorical_accuracy: 0.7555 - val_loss: 0.6373 - val_categorical_accuracy: 0.7835
Epoch 9/30
16/16 [==============================] - 641s 40s/step - loss: 0.6253 - categorical_accuracy: 0.7811 - val_loss: 0.5589 - val_categorical_accuracy: 0.8035
Epoch 10/30
16/16 [==============================] - 675s 43s/step - loss: 0.5616 - categorical_accuracy: 0.8047 - val_loss: 0.4769 - val_categorical_accuracy: 0.8370
Epoch 11/30
16/16 [==============================] - 636s 40s/step - loss: 0.5319 - categorical_accuracy: 0.8151 - val_loss: 0.4618 - val_categorical_accuracy: 0.8432
Epoch 12/30
16/16 [==============================] - 661s 42s/step - loss: 0.4452 - categorical_accuracy: 0.8466 - val_loss: 0.4119 - val_categorical_accuracy: 0.8597
Epoch 13/30
16/16 [==============================] - 648s 41s/step - loss: 0.4075 - categorical_accuracy: 0.8583 - val_loss: 0.4221 - val_categorical_accuracy: 0.8575
Epoch 14/30
16/16 [==============================] - 644s 40s/step - loss: 0.3678 - categorical_accuracy: 0.8732 - val_loss: 0.3288 - val_categorical_accuracy: 0.8910
Epoch 15/30
16/16 [==============================] - 672s 42s/step - loss: 0.3470 - categorical_accuracy: 0.8816 - val_loss: 0.3455 - val_categorical_accuracy: 0.8800
Epoch 16/30
16/16 [==============================] - 676s 43s/step - loss: 0.3202 - categorical_accuracy: 0.8890 - val_loss: 0.3045 - val_categorical_accuracy: 0.9005
```

```
Epoch 17/30
16/16 [==============================] - 653s 41s/step - loss: 0.2870 - categorical_accuracy: 0.9027 - val_loss: 0.3032 - val_categorical_accuracy: 0.8915
Epoch 18/30
16/16 [==============================] - 691s 43s/step - loss: 0.2609 - categorical_accuracy: 0.9094 - val_loss: 0.2576 - val_categorical_accuracy: 0.9153
Epoch 19/30
16/16 [==============================] - 682s 44s/step - loss: 0.2164 - categorical_accuracy: 0.9254 - val_loss: 0.2633 - val_categorical_accuracy: 0.9162
Epoch 20/30
16/16 [==============================] - 671s 42s/step - loss: 0.2108 - categorical_accuracy: 0.9283 - val_loss: 0.2479 - val_categorical_accuracy: 0.9202
Epoch 21/30
16/16 [==============================] - 682s 43s/step - loss: 0.1929 - categorical_accuracy: 0.9343 - val_loss: 0.2516 - val_categorical_accuracy: 0.9210
Epoch 22/30
16/16 [==============================] - 653s 41s/step - loss: 0.1835 - categorical_accuracy: 0.9369 - val_loss: 0.2536 - val_categorical_accuracy: 0.9155
Epoch 23/30
16/16 [==============================] - 686s 43s/step - loss: 0.1548 - categorical_accuracy: 0.9467 - val_loss: 0.2344 - val_categorical_accuracy: 0.9252
Epoch 24/30
16/16 [==============================] - 655s 41s/step - loss: 0.1525 - categorical_accuracy: 0.9478 - val_loss: 0.2316 - val_categorical_accuracy: 0.9247
Epoch 25/30
16/16 [==============================] - 668s 42s/step - loss: 0.1348 - categorical_accuracy: 0.9526 - val_loss: 0.2283 - val_categorical_accuracy: 0.9275
Epoch 26/30
16/16 [==============================] - 671s 42s/step - loss: 0.1170 - categorical_accuracy: 0.9608 - val_loss: 0.2298 - val_categorical_accuracy: 0.9283
Epoch 27/30
16/16 [==============================] - 637s 40s/step - loss: 0.1286 - categorical_accuracy: 0.9575 - val_loss: 0.2174 - val_categorical_accuracy: 0.9310
Epoch 28/30
16/16 [==============================] - 666s 42s/step - loss: 0.1260 - categorical_accuracy: 0.9551 - val_loss: 0.2058 - val_categorical_accuracy: 0.9358
Epoch 29/30
16/16 [==============================] - 646s 41s/step - loss: 0.1103 - categorical_accuracy: 0.9617 - val_loss: 0.2009 - val_categorical_accuracy: 0.9375
Epoch 30/30
16/16 [==============================] - 663s 42s/step - loss: 0.0984 - categorical_accuracy: 0.9643 - val_loss: 0.1977 - val_categorical_accuracy: 0.9360
```

Figure 10: Epoch

4.3 Experimental Experience

We have implemented Xception CNN models in our work.

TABLE 2: ACCURACY FOR TRAINING AND VALIDATION SET.

Model	Training Set	Validation Set
Xception	**94.89%**	**94.99%**

4.4 Plot the loss and accuracy of the model

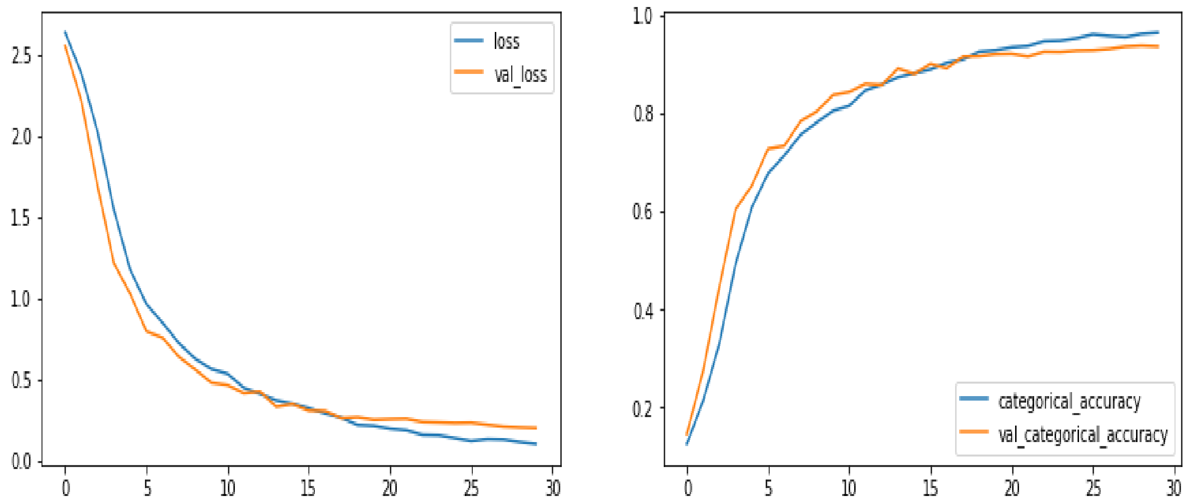

Figure 11: Visualization of model training and validation accuracy

CHAPTER 5

CONCLUSION

5.1 Conclusion

The current research looks at image processing approaches for dragon fruit that is connected to automatic color detection. Picture acquisition, sorting, feature extraction, image preprocessing, and classification are all part of the process. The creation of automated detection systems that use advanced computer technology to aid in the early detection of dragon fruit color and provide useful information for its control. We'd like to improve our ability to detect things quickly. Dragon is quite possibly the most widely recognized natural product on the planet. We used the Xception Model.

5.2 Future Enhancement

In future, in this model, and we use Color-based model classification for getting Better Accuracy. Accuracy may be improved by enhancing dataset categorization, modifying feature extraction strategies, and expanding image processing and classification techniques, which we intend to do in the future. Future applications will be created based on this research.

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